Mapping France's land-cover at 10 m every year. Lessons learned and future improvements.

Jordi INGLADA, Arthur VINCENT, Vincent THIERION

[2019-05-16 Thu]

CESBIO

Outline

1. Intro
2. Methodology
3. Product validation
4. Main limitations and user feedback
5. What's next

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jordi.inglada@cesbio.eu

Intro

Theia is the French Land Data Center

- Created at the end of 2012 by 9 French public institutions involved in Earth observation and environmental sciences
- Facilitate the use of images resulting from the spatial observation of continental surfaces
- Three pillars
    1. a Spatial Data Infrastructure (SDI) distributed among several actors,
    2. a network of Scientific Expertise Centers (SEC),
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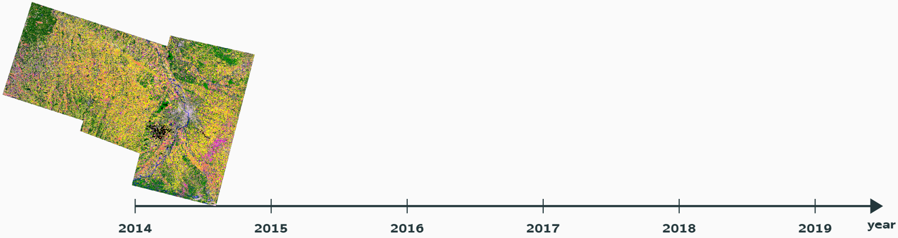
Land Cover SEC

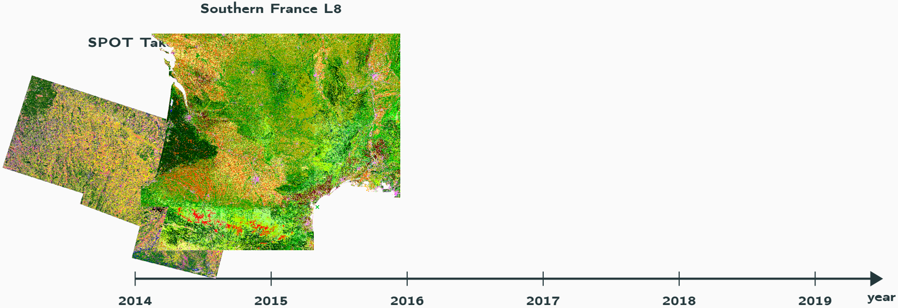
- Define and develop automatic algorithms to produce land cover maps using satellite imagery
- Production of national maps (mainland France then Europe?)

Timeline of the productions

SPOT Take5



Timeline of the productions



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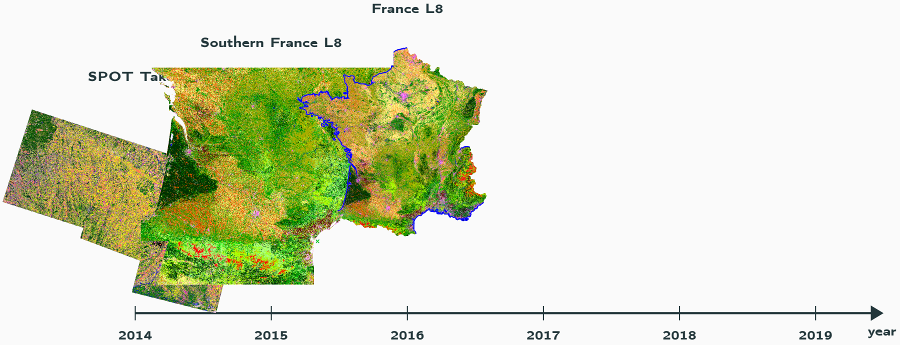

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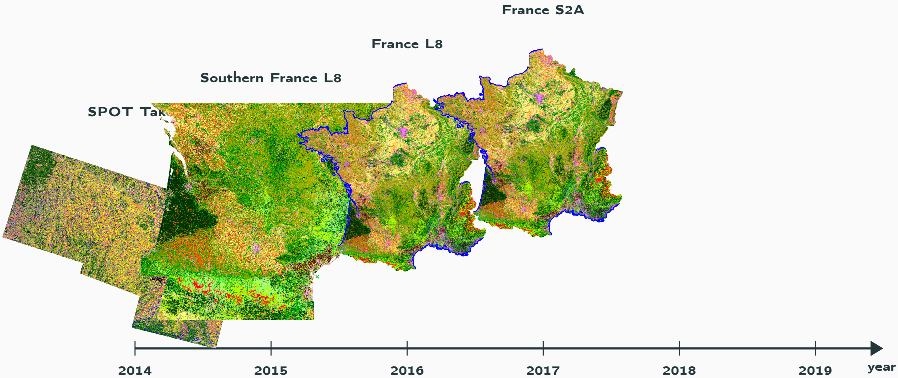

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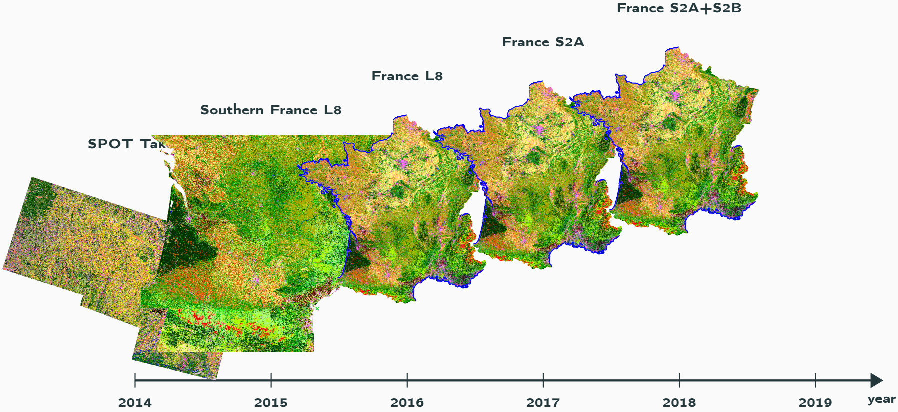

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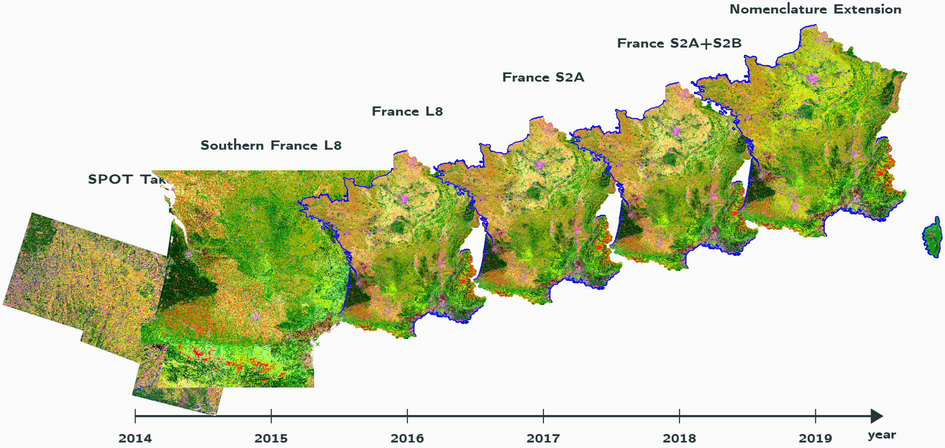

Nomenclature

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  1. Summer Crops
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- Other
  16. Water bodies
  17. Glaciers and eternal snow
- Extension to 23 classes
  - Summer Crops: Soybean, Sunflower, Corn, Rice, Root/tuber
  - Winter Crops: Rapeseed, Straw cereals, Protein crops

Methodology

Supervised classification

- Pixel based, time profiles of reflectances and spectral indices
- All available images (regardless of cloud cover) are used
- Random Forests: fast, robust to label noise, state of the art for high dimensional non contextual classification

Inglada, J., Vincent, A., Arias, M., Tardy, B., Morin, D., & Rodes, I., Operational high resolution land cover map production at the country scale using satellite image time series, **Remote Sensing, 9(1), 95 (2017)**. http://dx.doi.org/10.3390/rs901009

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Reference data

- Annual updates over $543,939 km^2$ can not rely on field surveys
- Fusion of out-of-date and heterogeneous DBs
  - Corine Land Cover by default
  - LPIS for agriculture
  - National Topo Data Base for forests
  - Urban Atlas for artificial surfaces

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The problem

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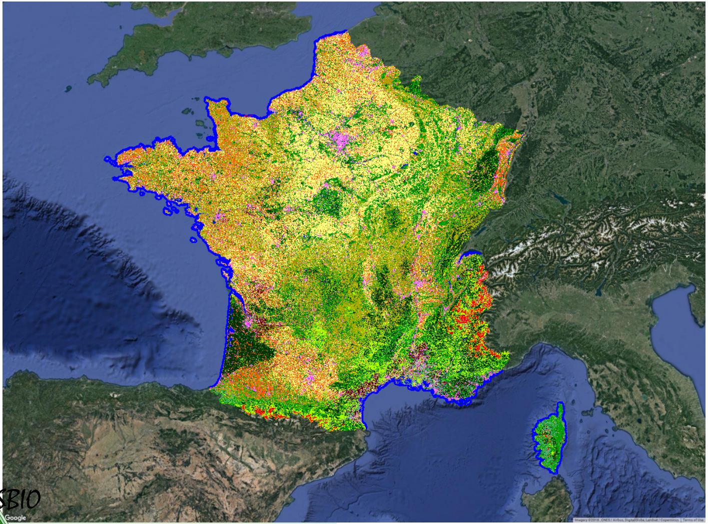

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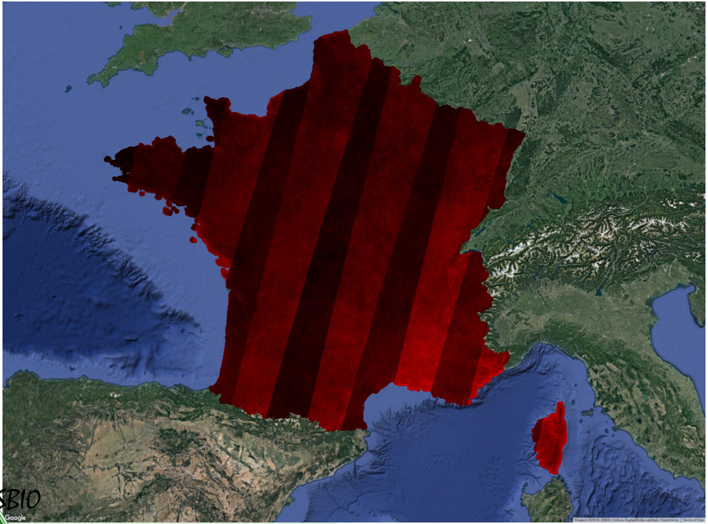

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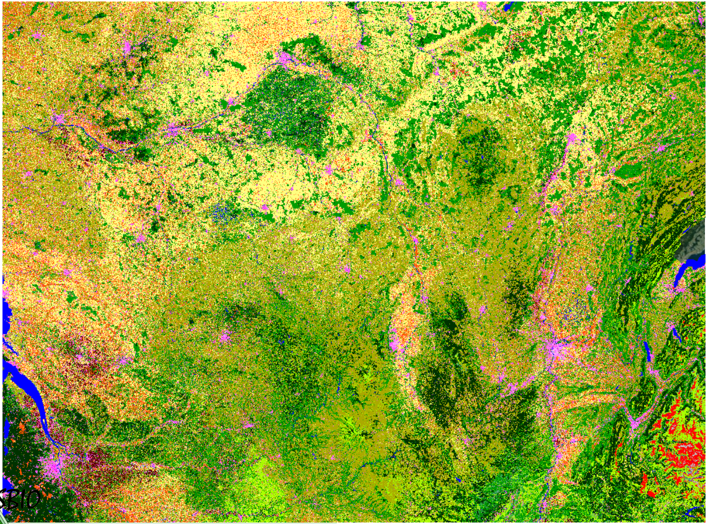

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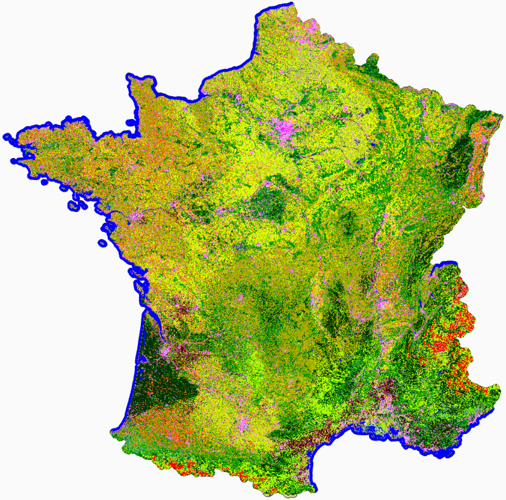
One solution

- Use cloud and cloud-shadow masks to flag invalid pixels
- Temporal gap-filling by linear interpolation is enough for classification purposes
- Interpolation allows us to resample onto a regular time grid
- All the pixels have now the same "virtual dates"

Eco-climatic stratification



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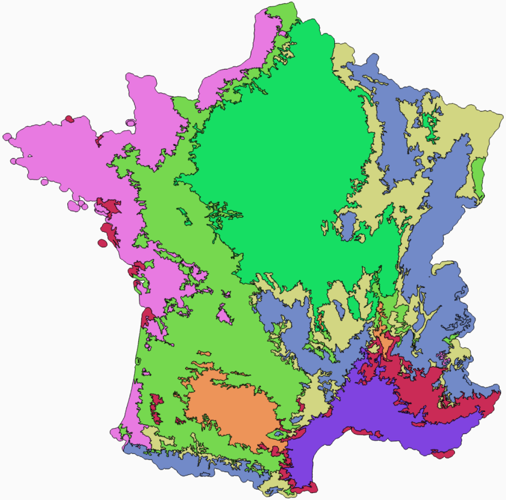

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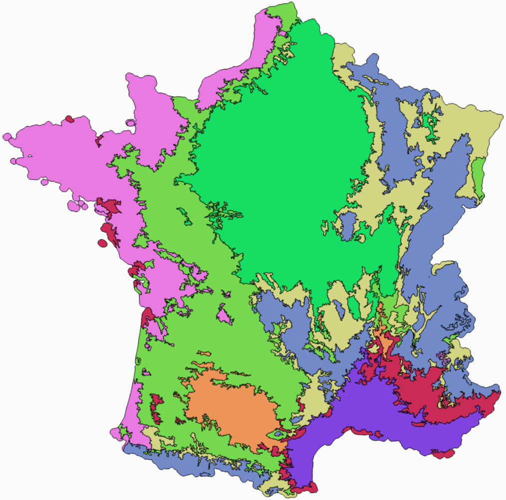
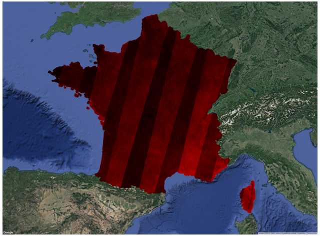
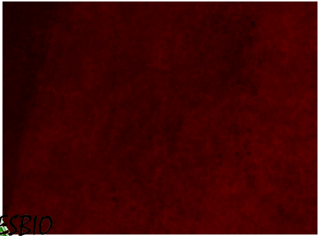


- Use one different classifier for each climatic region
- Up to 5% accuracy increase

Validity





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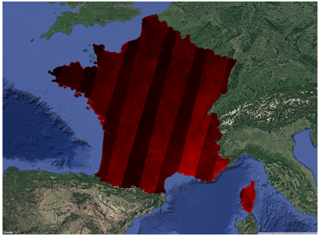
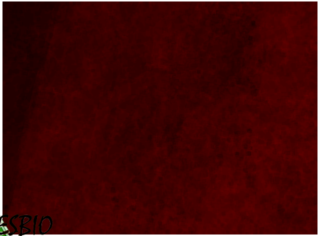
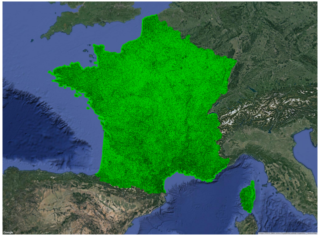
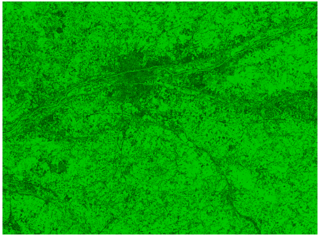




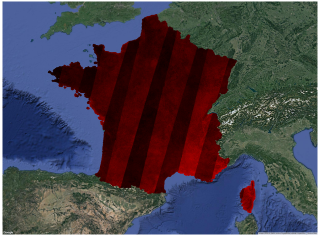
Confidence

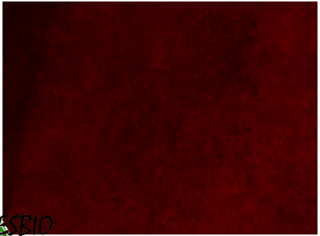




Additional products

Validity





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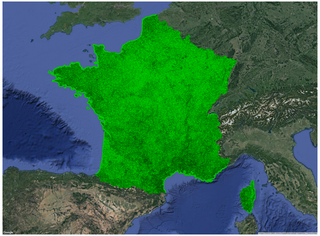
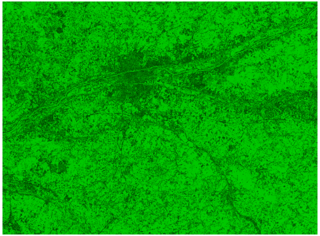
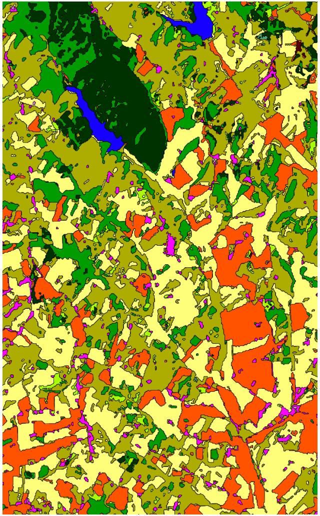
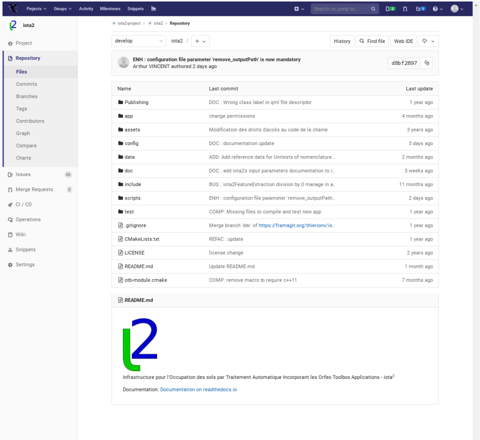


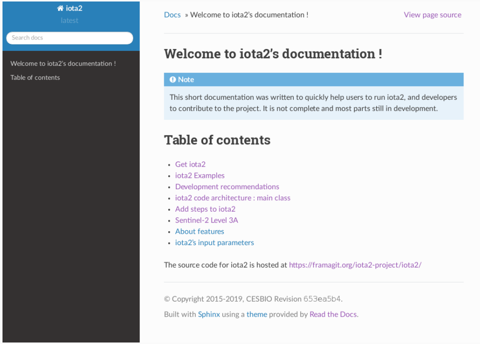


Vector data



iota2

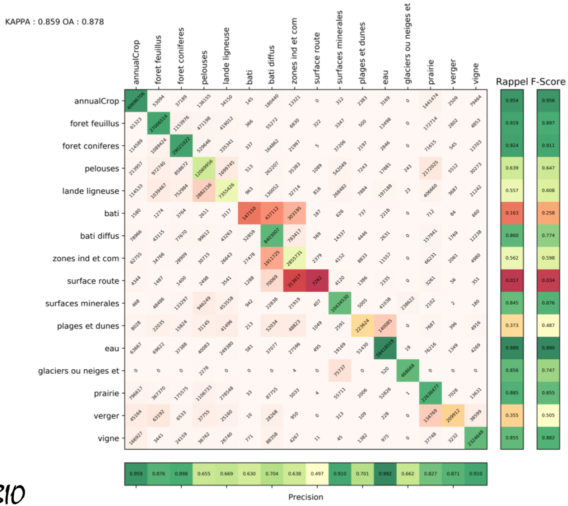




- Free software: GNU Affero General Public License v3.0.
- `https://framagit.org/iota2-project/iota2.git`

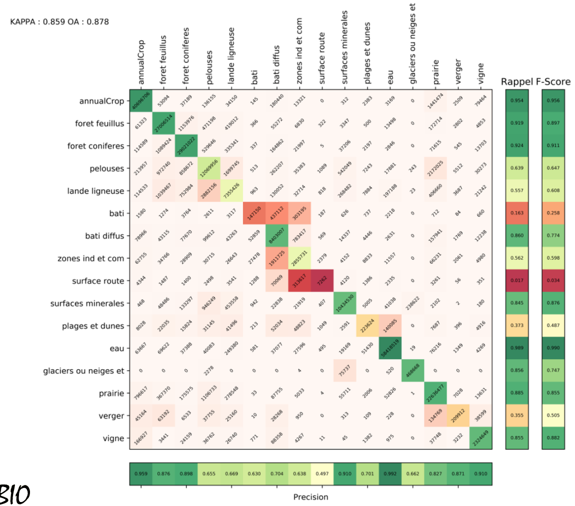
Product validation

Confusion matrix



Classical Machine Learning metrics

Confusion matrix



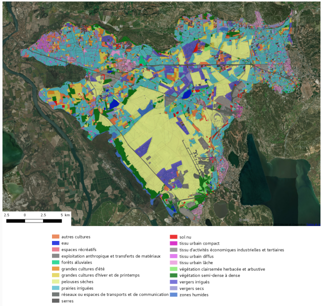
Pros & cons

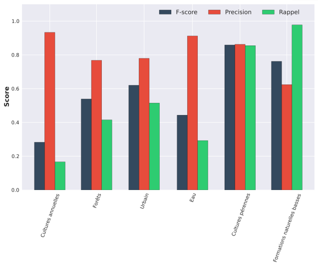
- Covers the whole area
- Same nomenclature as the map

- Reference data is noisy and out of date
- Although train/validation split is rigorous, they come from the same source

Independent sources

Ground surveys, other DBs





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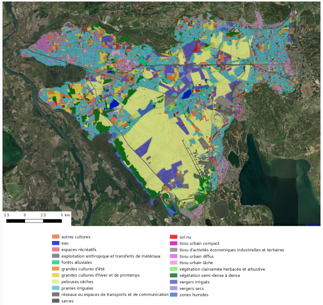

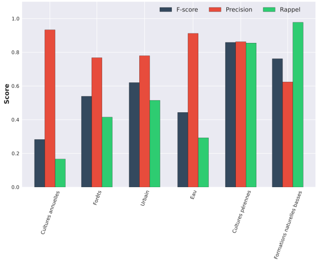

Pros & cons

- Data is clean and accurate
- Provided by users

- Different nomenclature
- Covers a small part of the territory

Independent expert validation

- SIRS is the Corine Land Cover producer for France
- In charge of the validation of several Copernicus Land Monitoring Service products
  - High Resolution Layers
  - Urban Atlas

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  2. Plausibility analysis between operator's interpretation and S2 map

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  - High Resolution Layers
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- Validation protocol on 1428 points over Metropolitan France
  1. Blind interpretation without knowledge of the S2 map
  2. Plausibility analysis between operator's interpretation and S2 map
- The map reaches the acceptability threshold for this kind of products (>85%)
  - 81.4 +/- 3.68% (blind)
  - 91.7 +/- 1.25% (plausibility)
- Validation report: `https://frama.link/oso-sirs-validation`

Main limitations and user feedback

Poor performances on some classes

Natural vegetation

- Forest → Moorland → Grassland → Bare rock
  - a continuous gradient
- the classes are very similar
- the reference data imposes arbitrary boundaries depending on the area and the context.

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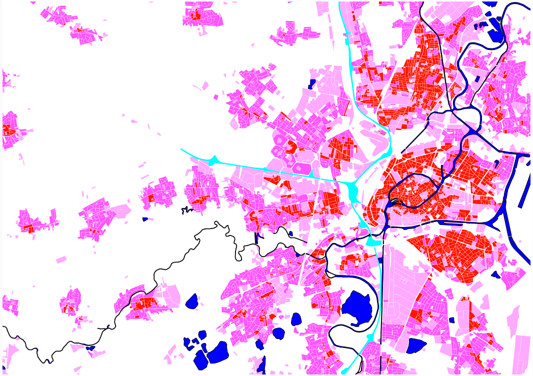
Urban areas



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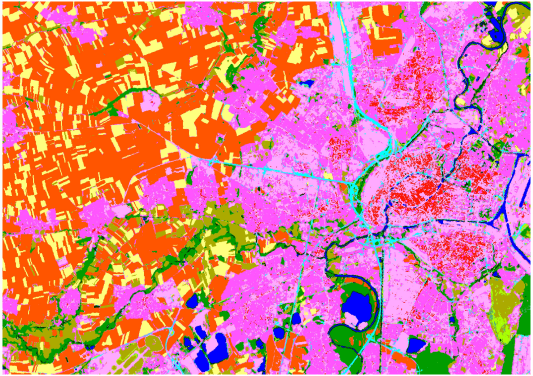

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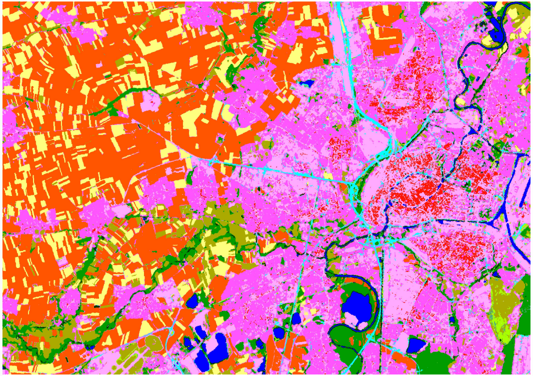
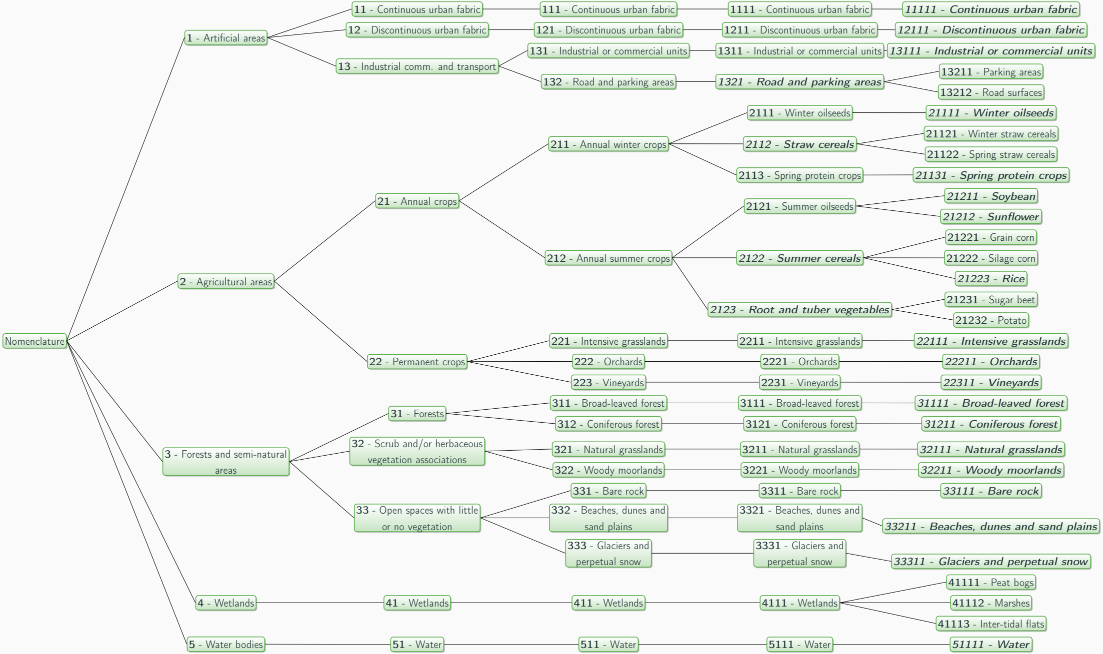


- Contextual classification is needed


Nomenclature
1 - Artificial areas
11 - Continuous urban fabric
111 - Continuous urban fabric
1111 - Continuous urban fabric
11111 - Continuous urban fabric
12 - Discontinuous urban fabric
121 - Discontinuous urban fabric
1211 - Discontinuous urban fabric
12111 - Discontinuous urban fabric
13 - Industrial comm. and transport
131 - Industrial or commercial units
1311 - Industrial or commercial units
13111 - Industrial or commercial units
132 - Road and parking areas
1321 - Road and parking areas
13211 - Parking areas
13212 - Road surfaces
2 - Agricultural areas
21 - Annual crops
211 - Annual winter crops
2111 - Winter oilseeds
21111 - Winter oilseeds
2112 - Straw cereals
21121 - Winter straw cereals
21122 - Spring straw cereals
2113 - Spring protein crops
21131 - Spring protein crops
212 - Annual summer crops
2121 - Summer oilseeds
21211 - Soybean
21212 - Sunflower
2122 - Summer cereals
21221 - Grain corn
21222 - Silage corn
21223 - Rice
2123 - Root and tuber vegetables
21231 - Sugar beet
21232 - Potato
22 - Permanent crops
221 - Intensive grasslands
2211 - Intensive grasslands
22111 - Intensive grasslands
222 - Orchards
2221 - Orchards
22211 - Orchards
223 - Vineyards
2231 - Vineyards
22311 - Vineyards
3 - Forests and semi-natural areas
31 - Forests
311 - Broad-leaved forest
3111 - Broad-leaved forest
31111 - Broad-leaved forest
312 - Coniferous forest
3121 - Coniferous forest
31211 - Coniferous forest
32 - Scrub and/or herbaceous vegetation associations
321 - Natural grasslands
3211 - Natural grasslands
32111 - Natural grasslands
322 - Woody moorlands
3221 - Woody moorlands
32211 - Woody moorlands
33 - Open spaces with little or no vegetation
331 - Bare rock
3311 - Bare rock
33111 - Bare rock
332 - Beaches, dunes and sand plains
3321 - Beaches, dunes and sand plains
33211 - Beaches, dunes and sand plains
333 - Glaciers and perpetual snow
3331 - Glaciers and perpetual snow
33311 - Glaciers and perpetual snow
4 - Wetlands
41 - Wetlands
411 - Wetlands
4111 - Wetlands
41111 - Peat bogs
41112 - Marshes
41113 - Inter-tidal flats
5 - Water bodies
51 - Water
511 - Water
5111 - Water
51111 - Water

Suitability to change detection

Annual maps

- Invite users to compute pixel-wise differences
- LC changes smaller than 5%, but 10% error in the map
- Errors are not random: transitions between similar classes

Annual maps

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Solutions?

- Confidence maps can be used to filter the detected changes
- Distribute probability maps for each class
- ???

What’s next

Current limitations of CNN

- Need for dense annotations
- Computationally intensive:
  - Accuracy per Joule? / Carbon footprint of the map!
  - Accuracy per € in your cloud provider bill · · ·

Contextual classification

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Comparing Deep Convolutional Neural Networks To Handcrafted Contextual Features For Large Scale Land Cover Mapping

Thursday, May 16, 2019

5:20 PM - 7:00 PM

South Hall - Floor 0

Poster Presentation Area C - Board 334

Contextual classification

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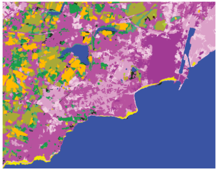
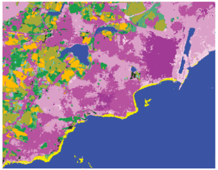
Auto Context RF

Auto-Context



MLP-Unet



	Kappa	OA
T31TDN		
RF (pixel)	89,53 %	91,87 %
AC	89,42 %	92,19 %
MLP_Unet	89,82 %	92,49 %
T30TXQ		
RF (pixel)	82,87 %	90,61 %
AC	86,90 %	93,31 %
MLP_Unet	87,74 %	93,77 %
T31TGK		
RF (pixel)	64,24 %	71,01 %
AC	66,66 %	73,10 %
MLP_Unet	67,20 %	73,67 %
T31UDQ		
RF (pixel)	75,02 %	79,40 %
AC	84,70 %	88,70 %
MLP_Unet	86,13 %	89,78 %

Conclusions

- Similar result in terms of Overall Accuracy
- CNN provides finer disctinction in urban areas
- Geometry of the CNN result is blurry
- Computation times are much slower

Method	Training time/CPU
RF	≈25h
Auto-Context	≈80h
MLP-Unet	≈3300h

Reducing the dependence on up-to-date training data

Leverage past image time series

- Reference data comes from existing DBs
- Train classifiers on past images and outdated references
- Perform model fusion
- Apply Domain Adaptation techniques (Optimal Transport)

Tardy, B., Inglada, J., & Michel, J., Fusion approaches for land cover map production using high resolution image time series without reference data of the corresponding period, **Remote Sensing, 9(11), 1151 (2017).** http://dx.doi.org/10.3390/rs9111151

Tardy, B., Inglada, J., & Michel, J., Assessment of optimal transport for operational land-cover mapping using high-resolution satellite images time series without reference data of the mapping period, **Remote Sensing, 11(9), 1047 (2019).** http://dx.doi.org/10.3390/rs11091047

Other improvements

Using several years of images

- But keeping yearly updates
- Better description of long term trends
- Better characterization of similar classes
- But huge data volumes!

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Sentinel-1

- Complementary with optical measures → better discrimination
- Increase data availability in cloudy areas
- But huge data volumes
- Experiments show small improvements so far

Q&A

https://frama.link/lps19

jordi.inglada@cesbio.eu